© International Journal of Combinatorial Optimization Problems and Informatics, Vol. 9, No. 2, May-Aug 2018, pp. 11-24. ISSN: 2007-1558.

Forecast of the Wind Speed using the Regional Atmospheric Modeling System (RAMS) and Weather Research and Forecasting (WRF) models

Ramón Lira-Argüello[1], Miguel A. Ruiz-Jaimes[2], Ubaldo Miranda Miranda[2], Ricardo Saldaña Flores[2], Ocotlán Díaz-Parra[3], Alejandro Fuentes-Penna[3], Yadira Toledo-Navarro[2]
[1] *Instituto Nacional de Electricidad y Energías Limpias, México.*
[2] *Universidad Politécnica del Estado de Morelos, México.*
[3] *Universidad Autónoma del Estado de Hidalgo, México.*
ramon.lira@iie.org.mx

Abstract. Physical, statistical models or a combination of both are used for the wind power prediction. Physical models considered meteorological and geophysical data to determine the value of the speed of the wind and with this power generation; statistical models, on the other hand, used historical data of electric generation. The latter integrated wind speed obtained from a numerical model. If the wind speed is not forecast within a range of acceptable error, power generation forecast will be affected in a critical way. This study presents the development of a hardware-software infrastructure to provide a short-term wind forecast, 4 times a day using the model Regional Atmospheric Modeling System (RAMS) and the Weather Research and Forecasting (WRF) 1 km resolution in an area of 1344 km2 located in the South of the Isthmus of Tehuantepec, Oaxaca. From the models are obtained datasets at the height of 80 m. Databases used as initial conditions and frontier models are data from the Global Forecast System (GFS) of the National Centers for Environmental Prediction (NCEP) for a period of one year. As the technique of adjustment models of prognosis numerical of weather (NWP) was implemented Kalman filter algorithm trying to eliminate systematic errors that are generated when modeling at levels close to the Earth's surface. As an option of statistical models were 3 models Autoregressive Integrated Moving Average (ARIMA) using historical data of wind speed. Forecast of the wind speed of all configurations was validated by comparing it with data measured at 80 m with a weather station located in the area, which belongs to the National Institute of electricity and clean energies (INEEL). Chai and Draxler [4] recommended using more than one metric to validate the models. The statistics were used in this study: mean absolute deviation (MAD), the mean absolute error (MAE) and the root of the mean square error (RMSE). The results show that the best model of forecasting for the period of 5 days is the WRF with an average RMSE of 2.48 and MAE average of 1.7. Forecasts 24 hours the best choice turned out to be the Kalman filter applied to the outputs of the RAMS model. This model shows the mean values of RMSE 1.74 and MAE of 1.32. Taking into account these results were operationally configured models and in a geographical information system provided the best forecasts 4 times a day every 6 hour. As future work in the short term is planned to make the forecast of wind and comparison of actual power generation with the forecasted for the wind turbine KWT300 (300 kW) located within the Regional Centre of Technology (CERTE) of the INEEL.

Keywords: Wind speed forecast; wind power; NWP; Kalman filter

1 Introduction

In the year 2008 was approved the law for the use of renewable energies and the financing of the transition energy in Mexico who orders electricity generation with clean sources of 35% for 2024, 40% by 2035, and 50% by 2050. This is projected that the generation plants grow significantly year after year. At the end of the year 2012, the installed capacity - including all sources of energy - was 63745 MW of which 2000 MW corresponded to the power plants [26]. According to the Mexican Association of Wind Energy (AMDEE), in 2014 had 2551 MW installed and it is expected that by the end of 2015 is 3283 MW and for 2018, 10811 MW [2]. The increase of the wind power in electricity generation mix will gradually represent a higher percentage. This means that variations in the generation plants will have increasingly more significant and therefore impact will need to know in sufficient detail the variations in the short term.

Received Jan 24, 2018 / Accepted Feb 11, 2018

In Mexico the entity that regulates the power supply, and so it also controls suppliers, is the National Center for Energy Control (CENACE). Recently, the energy reform, its functions were updated, so it is one of their principal powers to operate the wholesale electric market in conditions that promote competition, efficiency, and impartiality, using optimum power stations, as well as import and export programs allocation and office to satisfy energy demand.

The implementation of these functions requires the CENACE to predict power generation of its power plants to properly control the dispatch, export, and import of energy. The generation of power plants depends on, among other variables, of the wind speed. The proposed system is intended to provide a forecast of the wind speed that serves as input to the forecasting of power generation system. Meteorological models produce data that normally do not coincide one-to-one with actual or measure the wind speed. Typically values monthly averages are compared to determine if a simulation is acceptable. Therefore, arises the use of two models and the creation of a combination of simultaneous results which can be achieved one better.

2 Methodology

For this research, it was chosen as the study area called Isthmus of Tehuantepec, located in the southwest of Mexico. It is the narrowest in the country between the Pacific Ocean and the Gulf of Mexico, the mountainous area of the Mother Mountains of the South is a gap of approximately 80 Km where the altitude of the central part reaches on average 250 m and is growing on all sides up to heights of 2000 m. For RAMS and WRF Mesoscale models have been considered three specified nested meshes as shown in Figure 1 and Table 1.

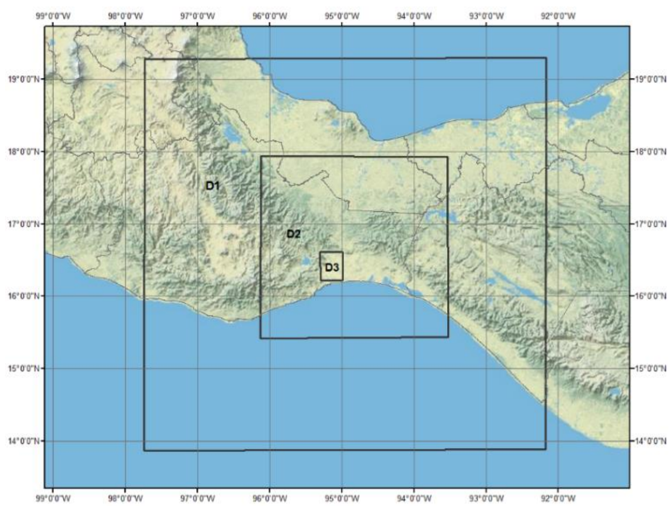

Fig. 1. Location of the domain 1 (D1), domain 2 (D2) and 3 (D3) configured RAMS and WRF.

Table 1. The spatial configuration of the RAMS and WRF model.

	D1	*D2*	*D3*
Approximate spatial expansion	Lat (13.88° - 19.28° N)	Lat (15.42° - 17.94° N)	Lat (16.21° - 16.61° N)
	Lon (97.74°-92.16° W)	Lon (96.12°-93.51° W)	Lon (95.29°-94.98° W)
Points in x	28	54	32
Points in y	28	54	42
Levels (z)	30	30	30
Spatial resolution	20 km	5 km	1 km

Data Input to Model

The Experiments consist of the prognosis of the first 5 days of each month from October 2015 to September 2016 since it is the period that includes data in an area of the Isthmus of Tehuantepec to 80 meters in height. GFS data downloaded from the page from the NCEP corresponding to 5 days of the forecast are used for RAMS and WRF model forecasts. ARIMA models use a period of 30 days of measured data as historical data, and they are forecast 5 days that they coincide with the predicted by meteorological models. Technique statistics of the result of the model (MOS) and the Kalman filter are applied to the RAMS and WRF model forecasts, these techniques are used for adjustment and improvement of data series.

Data to Validate Model

The surface data used in the verification of the forecasts were obtained from a meteorological station located on the Isthmus of Tehuantepec, Oaxaca. This station provides data relative humidity, 50 and 80 m wind speed, the direction of the wind at 50 to 80 meters, temperature, and pressure. The surface data used in the verification of the forecasts were obtained from a meteorological station located in the Isthmus of Tehuantepec, Oaxaca. This station provides data relative humidity, 50 and 80 m wind speed, the direction of the wind at 50 to 80 meters, temperature, and pressure. Measured data are transmitted via satellite to the INEEL servers in order to detect disturbances or failures in the system of data acquisition. Transmission in almost real time information is taken advantage of to be incorporated into forecasting system for use in the post-processing of the forecasts.

Measurement Towers have all certified MEASNET calibrated sensors and were installed taking into account the recommendations, standards, and requirements in wind measurement procedures established by this same organization with the aim of obtaining more reliable measured data.

The values of wind speed are taken every 2 seconds for the data acquisition system and averaged every 10 minutes; it is important to take into account that wind data that generated the NWP are not punctual data as those observed, but are interpolated horizontally and vertically from the modeled three-dimensional cells. The metering station used for the validation of the models shown in Figure 2 and has the geographic coordinates (16.5289 ° N, 95.0634 ° W).

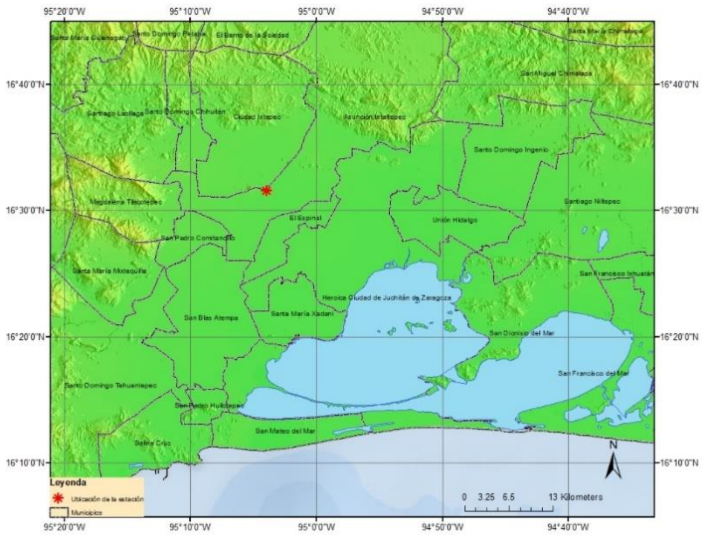

Fig. 2. Location of the anemometric station.

Regional Atmospheric Modeling System (RAMS)

The system of Regional atmospheric modeling (RAMS) is a limited area numerical prediction model, was developed to simulate the behavior of the atmosphere in a region of the planet, this region can cover from a full hemisphere to small regions to simulate the atmosphere boundary layer.

RAMS has been applied in national meteorological centers for weather forecasting and also for the study of atmospheric phenomena, such as hurricanes or storms (horizontal scales from 2 to 2000 km), however, it has enough power to simulate phenomena at a resolution of a few hundred meters.

The process of implementation of the model is organized in four main modules and covers since the preparation of the input data to the model that will serve as initial conditions to post processing and sample results.

- DATAPREP: Pre-processing module.
- ISAN (ISentropic ANalysis): Isoentropic analysis module.
- RAMS: Module for forecasting and assimilation.
- REVU (RAMS Evaluation and Visualization Utility): post-processing module.

Weather Research and Forecasting Model (WRF)

The model Weather Research and Forecasting (WRF) is a model of numerical prediction of the time of limited area non hydrostatic designed for research and atmospheric forecast, was developed at the National Center for atmospheric research (NCAR) and is operated by the University Corporation for Atmospheric Research (UCAR). Due to its non-hydrostatic condition and its sensitivity characteristics of topography, vegetation and land use can use in a variety of meteorological applications in scales of thousands of kilometers to hundreds of meters.

The architecture of the WRF model is very similar to the RAMS and the way run bullfighting is also very similar.
WRF numerical prediction model consists of several modules that comprise different features.

- GEOGRID: It allows to set the geographical area under study.
- UNGRIB: Prepare the initialization of the model data and boundary conditions.
- METGRID: Interpolates horizontally different meteorological field's extracted initialization of the model data.
- REAL: Performs vertical interpolation of data.

– WRF: It contains the physical equations of prognosis and diagnosis which allow making a prediction with a preset time horizon.

ARIMA

According to the research of Monteiro et al. [7], ARIMA (Auto-regressive integrated moving average) models were the first employees in the forecast of the wind speed; these early forecasts were made in horizons from 30 minutes up to 5 hours. The ARIMA are models based on the Box-Jenkins methodology and are composed of three components: the auto regressive model order, the order of the term Integrator or differentiator and the order of the moving average model.

The term Integrator or differentiator is added to give seasonal time series should not have it, the seasonality refers to that there is a pattern that is repeated with a period that is multiple of which exists in consecutive observations in particular time series.
With this operator, which is usually the differentiation, we can make a time series that is not stationary and be better represented by the ARMA. ARIMA(p,d,q) model where d stands for the number of differences applied and is recommended are also 1 or 2 small values. The ARIMA model can be represented as:

$$\emptyset_p(B)(1-B)^d X_t = \emptyset_0 + \theta_q + (B)\alpha_t \qquad (1)$$

Kalman Filter

The ensemble Kalman Filter (EnKF) or Kalman filter is to combine the system of data assimilation and prediction system, i.e. recursively combines observations with forecasts resent using a set of mathematical equations. This training model gives, as a result, the minimization of systematic errors that occur in the NWP to predict atmospheric variables in the near surface layers or to want to interpolate the data on height does not provide for the model [8].

The algorithm is executed in two phases, prediction and correction. In the prediction phase equations are a projection of the variable in time using the State of the variable at the time. The correction phase takes the predicted and observed values and realize an improvement of the estimate statistically minimizing the error.

Equations 2 and 3 are prognostic equations, these are estimates of the average of the State and covariance starting from, which can be initial estimates at the beginning and then from the outputs of the phase of correction [27].

$$\hat{X}_t^* = A\hat{X}_{t-1} \qquad (2)$$

$$P_t^* = AP_{t-1}A^t + Q \qquad (3)$$

For equation 2 the matrix A is constant and known but could also change for the different moments of t, X ̂_(t-1) is the best estimate of the previous media. In Equation 3 prediction variance P_t^* will be equal to the variance of the instant before P_(t-1) plus Q, Q represents the covariance of random perturbation of the process, this makes the uncertainty grows to be adding uncertainty in each iteration [27].

$$K_t = P_t^* H^T (HP_t^* H^T + R)^{-1} \qquad (4)$$

$$\hat{X}_t = \hat{X}_t^* + K_t(Z_t - H\hat{X}_t^*) \qquad (5)$$

$$P_t = (I - K_t H)P_t^* \qquad (6)$$

Other equations belong to the phase of correction, the equation 4 calculates the Kalman gain K_t, is a weighting of how much believed you as to and monitoring the forecast taking into account of observational noise R and the process noise covariance matrices, H is the matrix of observation or observational model.

Equation 5 calculates the correction of the average of the State X ̂_t by adding to the predicted average X ̂_t^* the product of the Kalman gain with the error of observation, observation error is obtained to the applying observational model the predicted state and subtract it to Z_t. The Equation 6 performs the correction of the covariance matrix and reduces the uncertainty taking into account the size of the observational noise and the noise of the process.

The Kalman filter has been applied in different areas, with the goal of eliminating systematic errors that accompany the data series, used in robotics to improve the signals of sensors, at Solera [27] is used to estimate the inflation persistence, in [9] is used to adjust the maximum and minimum temperatures giving a 90% improvement to the series of data.

Statistical Validation

Forecasts should be evaluated for its reliability, and there are several techniques to do this. However, these techniques should not be taken as a way to say that so successful is the prognosis, but use the experience and that somehow the indicated parameters allow to estimate and note that acceptance level has a prognosis or other. The forecast error is the difference of the predicted value, and the actual value, the techniques usually used for measuring forecast error are: the mean absolute deviation (MAD), the mean absolute error (MAE) and the root of the mean square error (RMSE).

The MAD indicates that so far are data regarding the arithmetic mean of the set and is calculated according to the equation 7, where N represents the total data number of the set, $\bar{X}$represents the average of the set and $|X_j - \bar{X}|$is the absolute value of deviations of the various X_j of $\bar{X}$.

$$MAD = \frac{\sum_{j=1}^{N} |x_j - \bar{x}|}{N} \tag{7}$$

MAE and RMSE indicators are calculated as 8 and 9 expressions indicate respectively:

$$MAE = \frac{1}{N}\sum_{j=1}^{N} |e_j| \tag{8}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{j=1}^{N} e_j^2} \tag{9}$$

The indicators recommended [4] to use as the RMSE and MAE for the evaluation of the performance of the model to use one would only provide a single projection of the errors in the model with emphasis to only one aspect of the characteristics of the error.

3 Results and Discussion

Interviews with CENACE staff in person and via email, it was that the period of forecast wind speed which is useful to them is 24 hours in advance and to a lesser extent to 5 or 7 days in advance. The forecast for the next 24 hours is used for programming and planning of the electrical firm of the next day. The planning in the medium term of 5 or 7 days in advance is commonly used for planning maintenance activities in a wind farm. Below, are the analysis and results of each method of prognosis for the two aforementioned periods. The models were classified in the following way:

- WRF: Outputs of the WRF model.
- RAMS: RAMS model outputs.
- ARIMA1: ARIMA model in the way (1,1,0) (0,1,1).
- ARIMA2: ARIMA model in the way (0,1,1) (0,1,1).
- ARIMA3: ARIMA model in the way (1,1,1) (0,1,1).
- WRFMOS: MOS implementation to the WRF model outputs.
- RAMSMOS: MOS implementation to the RAMS model outputs.
- WRF-KA3: Application of the Kalman filter to the WRF model outputs.
- RAMS-KA3: Application of the Kalman filter to the RAMS model outputs.

Five-day forecasts

Table 3 lists values of RMSE, MAE and MAD for each of the models in each 5 day forecast period and Figure 4 shows the behavior of the time series of the wind speed measured and forecasted the WRF model for the entire year of study.

Comparing tables 2 and 3 and Figure 3, shows that, although the WRF model only gives the best values for the period of September, is which yields the best average value of all periods, taking the maximum error in the period from January and the lowest in September, this represents greater reliability since, although other models give better results in some periods, the error increases in others.

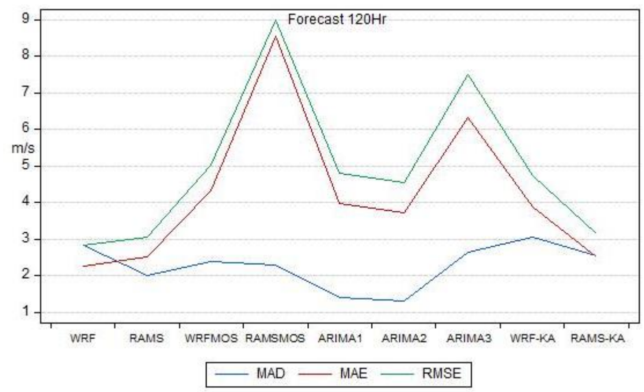

Fig. 3 RMSE value and average MAE of prognosis to 5 days of each model.

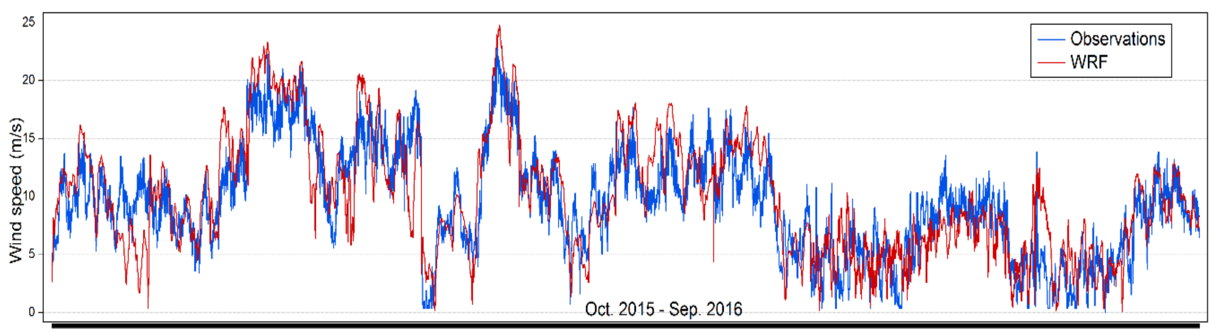

Fig. 4. Time series of the wind speed measured and forecasted by WRF.

Table 2. The average result of prognosis to 5 days of each model.

Model	RMSE	MAE	MAD
WRF	*2.82*	2.27	2.84
RAMS	*3.05*	2.50	2.00
WRFMOS	*5.01*	4.33	2.39
RAMSMOS	*8.98*	8.53	2.28
ARIMA1	*4.78*	3.97	1.41

ARIMA2	*4.53*	3.72	1.31
ARIMA3	*7.49*	6.32	2.63
WRF-KA3	*4.73*	3.88	3.06
RAMS-KA3	*3.13*	2.50	2.55

Table 3. Values of RMSE, MAE and MAD by the forecast for the next 5 days for each month.

Model	RMSE	MAE	MAD
WRF	*3.5*	*2.7*	*3.06*
RAMS	*4.63*	*3.75*	*2*
ARIMA1	*2.85*	*2.32*	*1.35*
ARIMA2	*2.85*	*2.31*	*1.35*
ARIMA3	*37.53*	*33.25*	*15.1*
WRFMOS	*3.45*	*2.64*	*2.73*
RAMSMOS	*9.45*	*8.84*	*2.68*
WRF-KA3	*3.15*	*2.34*	*2.74*
RAMS-KA3	*3.72*	*2.85*	*2.21*

Oct. 2015

Model	RMSE	MAE	MAD
WRF	2.43	1.93	2.72
RAMS	*2.34*	*1.92*	*2.29*
ARIMA1	*4.03*	*3.57*	*1.25*
ARIMA2	*2.85*	*2.31*	*1.35*
ARIMA3	*3.01*	*2.57*	*1.12*
WRFMOS	*3.36*	*2.85*	*2.46*
RAMSMOS	*8.36*	*7.93*	*2.24*
WRF-KA3	*2.03*	*1.57*	*2.52*
RAMS-KA3	*2.51*	*1.96*	*2.82*

Nov. 2015

Model	RMSE	MAE	MAD
WRF	3.16	2.57	3.83
RAMS	*3.27*	*2.94*	*1.95*
ARIMA1	*8.13*	*6.41*	*1.88*
ARIMA2	*7.16*	*5.61*	*1.14*
ARIMA3	*6.6*	*4.96*	*1.2*
WRFMOS	*7.13*	*6.66*	*2.5*
RAMSMOS	*12.41*	*12.03*	*2.42*
WRF-KA3	*4.11*	*3.54*	*3.78*
RAMS-KA3	*2.71*	*1.95*	*2.22*

Dec. 2015

Model	RMSE	MAE	MAD
WRF	3.62	2.86	2.89
RAMS	*3.46*	*2.91*	*1.48*
ARIMA1	*4.98*	*4.56*	*1.05*
ARIMA2	*5.01*	*4.59*	*1.05*
ARIMA3	*4.83*	*4.4*	*1.05*
WRFMOS	*6.59*	*5.9*	*2.39*
RAMSMOS	*9.18*	*8.75*	*2.27*
WRF-KA3	*8.59*	*7.18*	*4.58*
RAMS-KA3	*2.71*	*2.16*	*1.4*

Jan. 2016

Model	RMSE	MAE	MAD
WRF	2.51	2.03	5.96
RAMS	*2.93*	*2.44*	*5.3*
ARIMA1	*8.19*	*6.33*	*1.08*
ARIMA2	*8.26*	*6.37*	*0.95*
ARIMA3	*9.17*	*7.2*	*0.9*
WRFMOS	*8.89*	*7.76*	*3.88*
RAMSMOS	*10.26*	*9.4*	*3.58*
WRF-KA3	*6.93*	*5.75*	*2.2*
RAMS-KA3	*2.07*	*1.57*	*5.98*

Feb. 2016

Model	RMSE	MAE	MAD
WRF	2.11	1.74	2.42
RAMS	*2.75*	*2.33*	*1.97*
ARIMA1	*2.33*	*1.86*	*1.02*
ARIMA2	*2.33*	*1.86*	*1.02*
ARIMA3	*2.54*	*1.97*	*1.02*
WRFMOS	*2.82*	*2.27*	*1.6*
RAMSMOS	*9.54*	*9.31*	*1.69*
WRF-KA3	*2.13*	*1.69*	*2.32*
RAMS-KA3	*1.85*	*1.44*	*2.25*

Mar. 2016

Model	RMSE	MAE	MAD
WRF	3.13	2.62	2.14
RAMS	*3.03*	*2.11*	*1.4*
ARIMA1	*3.44*	*2.98*	*1.47*
ARIMA2	*2.33*	*1.86*	*1.02*
ARIMA3	*4.07*	*3.58*	*1.64*
WRFMOS	*4.18*	*3.38*	*3.33*
RAMSMOS	*11.79*	*11.22*	*3.17*
WRF-KA3	*2.63*	*2.11*	*1.81*
RAMS-KA3	*2.64*	*2.09*	*1.45*

Apr. 2016

Model	RMSE	MAE	MAD
WRF	2.78	2.27	3.73
RAMS	*2.88*	*2.25*	*2.45*
ARIMA1	*8.35*	*6.73*	*2.39*
ARIMA2	*8.49*	*6.86*	*2.42*
ARIMA3	*7.76*	*6.17*	*2.3*
WRFMOS	*5.39*	*4.78*	*2.34*
RAMSMOS	*7.59*	*7.05*	*2.25*
WRF-KA3	*2.72*	*2.16*	*3.51*
RAMS-KA3	*2.26*	*1.81*	*2.51*

May 2016

Model	RMSE	MAE	MAD
WRF	3.07	2.52	1.4
RAMS	*3.36*	*2.76*	*1.09*
ARIMA1	*2.98*	*2.42*	*1.41*
ARIMA2	*2.97*	*2.42*	*1.41*
ARIMA3	*2.84*	*2.31*	*1.4*
WRFMOS	*3.26*	*2.61*	*1.88*
RAMSMOS	*4.84*	*4.34*	*1.79*
WRF-KA3	*7.62*	*6.3*	*3.24*
RAMS-KA3	*3.38*	*2.53*	*1.83*

Jun. 2016

Model	RMSE	MAE	MAD
WRF	2.55	2.09	1.26

Model	RMSE	MAE	MAD
WRF	3.17	2.44	2.14

Model	RMSE	MAE	MAD
WRF	1.85	1.46	2.51

RAMS	*3.85*	*3.38*	*1.29*
ARIMA1	*5.19*	*4.79*	*1.24*
ARIMA2	*5.18*	*4.78*	*1.24*
ARIMA3	*3.58*	*3.17*	*1.12*
WRFMOS	*2.81*	*2.21*	*1.77*
RAMSMOS	*8.16*	*7.9*	*1.68*
WRF-KA3	*2.22*	*1.74*	*1.71*
RAMS-KA3	*6.62*	*5.73*	*3.53*

Jul. 2016

RAMS	*2.12*	*1.69*	*0.96*
ARIMA1	*2.72*	*2.13*	*1.23*
ARIMA2	*2.81*	*2.22*	*1.23*
ARIMA3	*2.57*	*2.1*	*1.24*
WRFMOS	*7.72*	*7.1*	*2*
RAMSMOS	*10.77*	*10.5*	*1.85*
WRF-KA3	*9.31*	*7.52*	*4.57*
RAMS-KA3	*3.73*	*3.04*	*1.69*

Aug. 2016

RAMS	*1.96*	*1.58*	*1.83*
ARIMA1	*4.16*	*3.48*	*1.54*
ARIMA2	*4.16*	*3.48*	*1.54*
ARIMA3	*5.41*	*4.15*	*3.49*
WRFMOS	*4.47*	*3.79*	*1.82*
RAMSMOS	*5.49*	*5.06*	*1.77*
WRF-KA3	*5.3*	*4.64*	*3.76*
RAMS-KA3	*3.4*	*2.86*	*2.76*

Sep. 2016

Forecasts 24 hours

Data of table 5 shows the best values for model WRF-KA3 during October, March, may and July, for the period of November, December, January, February and June that behaves best is RAMS WRF-KA3, the ARIMA1 model is the best for the period of April and the WRF obtains the best values for August and September.

Table 4 and Figure 5 shows the average values for each model, and you can see that the best values are obtained with the model RAMS-KA3. This same model is that remains constant in all periods with the maximum value of RMSE MAE in May and the minimum in February.

Table 4. The forecast average result within 24 hours of each model.

Model	RMSE	MAE	MAD
WRF	*2.48*	1.74	1.63
RAMS	*2.78*	2.31	0.94
WRFMOS	*3.86*	4.22	2.20
RAMSMOS	*8.39*	8.53	2.21
ARIMA1	*2.81*	2.37	1.20
ARIMA2	*2.84*	2.40	1.13
ARIMA3	*3.53*	2.98	1.66
WRF-KA3	*3.07*	2.25	2.43
RAMS-KA3	*1.74*	1.33	1.23

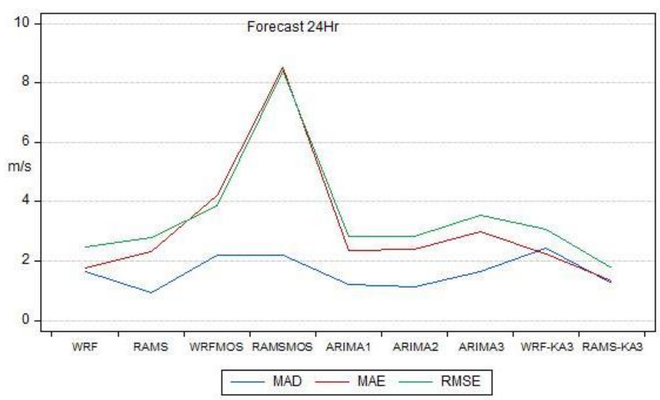

Fig. 5. RMSE value and average MAE's prognosis within 24 hours of each model.

Table 5. Values of RMSE, MAE and MAD by the forecast for the next 24 hours for each month.

Model	RMSE	MAE	MAD
WRF	*2.15*	*1.34*	*1.65*
RAMS	*2.87*	*2.12*	*0.66*
ARIMA1	*2.91*	*2.54*	*1.04*
ARIMA2	*2.9*	*2.54*	*1.04*
ARIMA3	*12.53*	*11.28*	*5.32*
WRFMOS	*1.81*	*1.47*	*1.87*
RAMSMOS	*9.11*	*8.83*	*1.81*
WRF-KA3	*1.71*	*1.29*	*1.8*
RAMS-KA3	*2.07*	*1.59*	*0.97*

Oct. 2015

Model	RMSE	MAE	MAD
WRF	2.33	1.41	1.03
RAMS	*2.61*	*2.22*	*0.61*
ARIMA1	*2.66*	*2.3*	*1.07*
ARIMA2	*2.9*	*2.54*	*1.04*
ARIMA3	*1.95*	*1.62*	*1*
WRFMOS	*4*	*2.85*	*2.46*
RAMSMOS	*6.72*	*7.93*	*2.24*
WRF-KA3	*1.41*	*1.13*	*1.53*
RAMS-KA3	*1.21*	*0.98*	*0.96*

Nov. 2015

Model	RMSE	MAE	MAD
WRF	3.63	1.76	2.02
RAMS	*2.47*	*2.25*	*0.54*
ARIMA1	*2.7*	*2.23*	*1.35*
ARIMA2	*2.48*	*1.99*	*0.88*
ARIMA3	*2*	*1.63*	*0.95*
WRFMOS	*6.04*	*6.66*	*2.5*
RAMSMOS	*12.34*	*12.03*	*2.42*
WRF-KA3	*4.26*	*3.32*	*2.42*
RAMS-KA3	*1.65*	*1.33*	*0.82*

Dec. 2015

Model	RMSE	MAE	MAD
WRF	4.09	1.88	4.74
RAMS	*1.98*	*1.7*	*1.2*
ARIMA1	*4.17*	*3.88*	*1.03*
ARIMA2	*4.21*	*3.92*	*1.03*
ARIMA3	*4.01*	*3.7*	*1.03*
WRFMOS	*7.95*	*7.4*	*2.39*
RAMSMOS	*7.13*	*8.75*	*2.27*
WRF-KA3	*9.3*	*6.35*	*8.04*
RAMS-KA3	*1.37*	*0.99*	*1.21*

Jan. 2016

Model	RMSE	MAE	MAD
WRF	2.61	2.26	1.46
RAMS	*1.89*	*1.59*	*1.55*
ARIMA1	*4.44*	*3.9*	*0.99*
ARIMA2	*4.19*	*3.7*	*0.86*
ARIMA3	*3.15*	*2.83*	*0.76*
WRFMOS	*4.27*	*7.76*	*3.88*
RAMSMOS	*7.77*	*9.4*	*3.58*
WRF-KA3	*2.4*	*1.57*	*1.01*
RAMS-KA3	*0.87*	*0.65*	*2.13*

Feb. 2016

Model	RMSE	MAE	MAD
WRF	1.41	1.02	1.12
RAMS	*3.16*	*2.67*	*1.15*
ARIMA1	*2.01*	*1.74*	*1.02*
ARIMA2	*2.01*	*1.74*	*1.01*
ARIMA3	*1.69*	*1.44*	*1.01*
WRFMOS	*2.1*	*2.27*	*1.6*
RAMSMOS	*10.53*	*9.31*	*1.69*
WRF-KA3	*1.13*	*0.86*	*1.09*
RAMS-KA3	*1.38*	*1.07*	*0.68*

Mar. 2016

Model	RMSE	MAE	MAD
WRF	2.78	2.39	1.22
RAMS	*1.99*	*1.59*	*0.43*
ARIMA1	*1.52*	*1.26*	*1.28*
ARIMA2	*2.01*	*1.74*	*1.01*
ARIMA3	*1.54*	*1.27*	*1.29*
WRFMOS	*5.86*	*3.38*	*3.33*
RAMSMOS	*9.07*	*11.22*	*3.17*
WRF-KA3	*1.61*	*1.21*	*1.3*
RAMS-KA3	*1.59*	*1.14*	*0.83*

Apr. 2016

Model	RMSE	MAE	MAD
WRF	1.97	1.58	1.74
RAMS	*4.05*	*3.26*	*1.09*
ARIMA1	*1.96*	*1.63*	*1.73*
ARIMA2	*1.99*	*1.66*	*1.73*
ARIMA3	*1.9*	*1.54*	*1.73*
WRFMOS	*4.31*	*4.78*	*2.34*
RAMSMOS	*9.01*	*7.05*	*2.25*
WRF-KA3	*1.34*	*1.11*	*2.1*
RAMS-KA3	*2.91*	*2.26*	*1.06*

May 2016

Model	RMSE	MAE	MAD
WRF	2.46	2.02	1.37
RAMS	*3.38*	*2.69*	*0.95*
ARIMA1	*3.31*	*2.65*	*1.25*
ARIMA2	*3.3*	*2.64*	*1.25*
ARIMA3	*3*	*2.36*	*1.24*
WRFMOS	*3.28*	*2.61*	*1.88*
RAMSMOS	*5.84*	*4.34*	*1.79*
WRF-KA3	*6.08*	*4.44*	*4.35*
RAMS-KA3	*2.12*	*1.61*	*1.41*

Jun. 2016

Model	RMSE	MAE	MAD
WRF	3.01	2.55	1.13
RAMS	*4.82*	*4.43*	*1.33*
ARIMA1	*2.74*	*2.35*	*1.07*
ARIMA2	*2.74*	*2.34*	*1.07*
ARIMA3	*1.92*	*1.54*	*1.05*
WRFMOS	*2.94*	*2.21*	*1.77*
RAMSMOS	*9.39*	*7.9*	*1.68*
WRF-KA3	*1.3*	*0.99*	*1.56*
RAMS-KA3	*2.03*	*1.47*	*2.08*

Jul. 2016

Model	RMSE	MAE	MAD
WRF	1.94	1.63	1.31
RAMS	*2.6*	*2.01*	*0.99*
ARIMA1	*2.73*	*2.08*	*1.12*
ARIMA2	*2.79*	*2.12*	*1.12*
ARIMA3	*3.17*	*2.69*	*1.2*
WRFMOS	*5.35*	*7.1*	*2*
RAMSMOS	*8.4*	*10.5*	*1.85*
WRF-KA3	*4.6*	*3.33*	*2.39*
RAMS-KA3	*2.08*	*1.57*	*0.95*

Aug. 2016

Model	RMSE	MAE	MAD
WRF	1.41	1.09	0.83
RAMS	*1.49*	*1.22*	*0.81*
ARIMA1	*2.55*	*1.87*	*1.47*
ARIMA2	*2.55*	*1.87*	*1.47*
ARIMA3	*5.51*	*3.88*	*3.33*
WRFMOS	*2.52*	*3.79*	*1.82*
RAMSMOS	*5.42*	*5.06*	*1.77*
WRF-KA3	*1.66*	*1.34*	*1.63*
RAMS-KA3	*1.62*	*1.26*	*1.65*

Sep. 2016

In Figure 6 you can see how the use of Kalman filter improves the RAMS model forecast results. In Figure 7 you can see series of predicted and measured wind data with the RAMS model by applying the filter of Kalman (RAMS-KA3) in each period and note how in every interaction the uncertainty increases, is for this reason that this technique works only for short periods of prognosis.

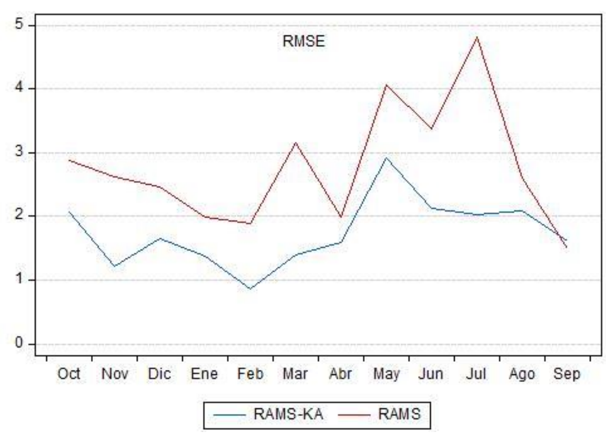

Fig. 6. RMSE value for the RAMS model and its fit with the filter of kalman for the 24-hour forecasts.

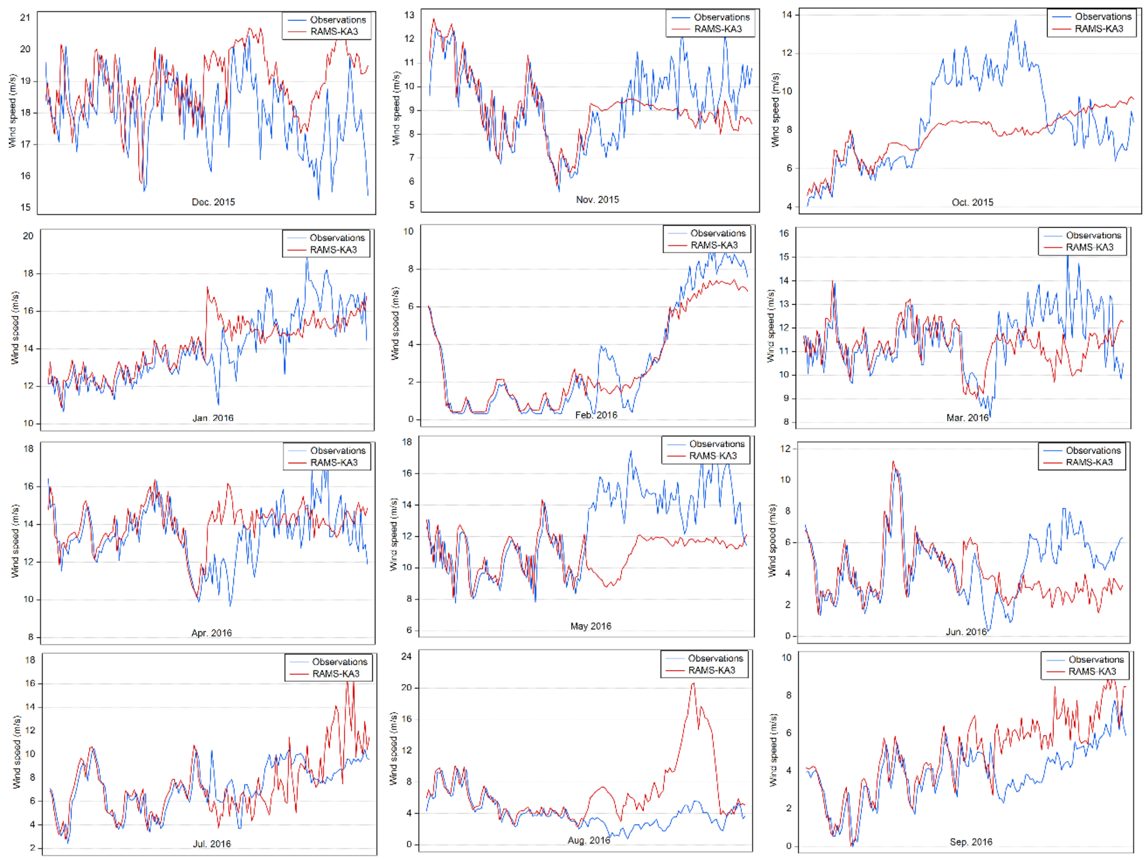

Fig. 7. Time series of the wind speed measured and forecasted with RAMS-KA3para each month.

4 Conclusions

According to the results, the best model of forecasting for the period of 5 days is the WRF with an average RMSE of 2.48 and a MAE average of 1.7. For the forecast for the next 24 hours, the best model proved to be the RAMS-KA3, which is the application of the Kalman filter to the outputs of the RAMS model, this model shows the mean values of RMSE 1.74 and an SSM from 1.32. These values are similar to the results shown by other works. CPRORE [6] presents an average RMSE value of 3 for forecasts of 7 days in advance, Chancham et al. [5] shows a value of MSE of between 1.6 and 5.83 in the analysis of annual average wind in 6 seasons, Louka et al. [23] shows RMSE of 3.36 and 2.25 for forecasts of 48 hours in advance.

Taking into account that according to the results the second best model for forecasting 5 days is the RAMS and the second best model for the 24 hours period is the WRF-KA3, inquiry system, will be available to the user forecasts of WRF and RAMS for the 5 day period and forecasts of RAMS-KA3 and WRF-KA3 for the 24 hour period. Many of wind generation forecasting

models that use the outputs of numerical models, generally use more than one forecast, since rarely numerical models coincide in the forecast.
Galanis et al. [13] argue that while the Kalman filter method has been widely used for the purpose of improving weather forecasting, the linear form of the algorithm may affect significantly results applied to the prediction of wind parameters since in some cases the wind speed time series are not continuous. Then while its application for the improvement of the prediction of the air temperature to be successful, may not be for the prediction of wind speed, this can be seen with the results of this work since, although the results of the 24-hour forecast improve with the Kalman filter used in the outputs of the RAMS, it is not so for the WRF outputs.

There are other methods that can be applied and which could improve performance, since the wind speed series are not linear, the method called Extended Kalman Filter or extended Kalman filter linearize the data series before applying the algorithm, also in other works such as the Galanis et al. [13] show the use of non-linear polynomials to the Kalman filter algorithm to improve predictions.

Conflict of Interest

The authors declare no conflict of interest.

References

1. ARW Modeling System User's Guide. (2016). 3rd ed. [e-book] National Center for Atmospheric Research. Retrieved from: http://www2.mmm.ucar.edu/ [Consulted on January 30, 2016].
2. AMDEE. Parques eólicos de México 2015. Available online: http://www.amdee.org/parques-eolicos-mexico-2015 (accessed on 08 Nov 2015).
3. Camilo Carrillo, José Cidrás, Eloy Díaz-Dorado, Andrés Felipe Obando-Montaño. An Approach to Determine the Weibull Parameters for Wind Energy Analysis: The Case of Galicia (Spain). Energies, 7, 2676-2700, **2014**.
4. CHAI, T. & DRAXLER, R. Root mean square error (RMSE) or mean absolute error (MAE)? – Arguments against avoiding RMSE in the literature. Geoscientific Model Development, 7(3), 1247-1250, **2014**.
5. CHANCHAM, C., WAEWSAK, J., CHAICHANA, T., LANDRY, M., & GAGNON, Y. Assessment of Onshore Wind Energy Potential Using Regional Atmospheric Modeling System (RAMS) for Thailand. Energy Procedia, 52, 487-496, **2014**.
6. CPRORE. Service of prediction of wind speed and short-term energy production. Retrieved www.cprore.com, **2015**.
7. C. MONTEIRO, R. BESSA, V. MIRANDA, A. BOTTERUD, J. WANG, AND G. CONZELMANN. Wind Power Forecasting: State-of-the-Art, **2009**.
8. DORADO, J; RUÍZ, J. F. Manual de usuario ApplyKalmanFilter_Linux. Group of Time and Climate Modeling. Subdirection of Meteorology. IDEAM, **2013**.
9. DORADO, J; RUÍZ, J. F. Implementación de filtros de kalman como método de ajuste a los modelos de pronóstico (GFS) de temperaturas máximas y mínima para algunas ciudades de Colombia. Group of Time and Climate Modeling. Subdirection of Meteorology. IDEAM, **2013**.
10. EUGENIA KALNAY. Atmospheric modeling, data assimilation and predictability. United States of America: Cambridge University Press, **2003**.
11. EDGAR DOLORES T, UBALDO MIRANDA M, RAMÓN LIRA A, RUBÉN I. CARIÑO G, J. MATÍAS MÉNDEZ P. Configuración del modelo Regional Atmospheric Modeling System (RAMS) para la generación de series de datos de viento en el Istmo de Tehuantepec. ONMAC 2014. México, **2014**.
12. FERNÁNDEZ JIMÉNEZ, L. Modelos avanzados para la predicción a corto plazo de la producción eléctrica en parques eólicos (Tesis Doctoral). Universidad de La Rioja, **2008**.
13. G. GALANIS, P. LOUKA, P. KATSAFADOS, G. KALLOS, AND I. PYTHAROULIS. Applications of Kalman Filters based on non-linear functions to numerical weather predictions. Annales Geophysicae, 24, 1-10, **2006**.
14. JORBA, C., O. Simulación de campos de viento de la Península Ibérica y el área geográfica de Catalunya con alta resolución espacial para distintas situaciones meteorológicas típicas. Tesis Doctoral. Programa de Doctorado en Ingeniería Ambiental, Universidad Politécnica de Catalunya. Barcelona, España. PP. 236, **2005**.

15. JOSÉ A. GARCIA-MOYA, A. CALLADO, C. SANTOS, D. SANTOS-MUÑOS Y J. SIMARRO. El sistema de predicción por conjuntos para el corto plazo del INM. Asociación meteorológica Española, Vol.5, Num. 16, pp. 22-27, **2007**.
16. JUNK, C., ALESSANDRINI, S., DELLE MONACHE, L. Analog-Based Ensamble Model Output Statistcs, Mon. Wheather Rev.143, 2909-2917, **2015**.
17. LUETHI D, ERB P, OTZIGER S. FKF: Fast Kalman Filter. R package version 0.1.1, URL http://CRAN.R-project.org/package=FKF, **2010**.
18. MATEOS FARFÁN EFRAÍN, SANTANA SEPÚLVEDA JULIO S., SALINAS PRIETO JOSÉ ANTONIO, PRIETO GONZÁLEZ RICARDO. Corrección estadística (MOS) al pronóstico atmosférico del modelo WRF. México: IMTA. Coordinación de Hidrología. Subcoordinación de Hidrometeorología, **2012**.
19. MEASURING NETWORK OF WIND ENERGY INSTITUTES (MEASNET). Power performance measurement procedure, Version 5. Retrieved from http:www.measnet.com, **2009**.
20. O. A. JARAMILLO, M.A. BORJA. Bimodal versos Weibull Wind Speed Distributions: An Analysis of Wind Energy Potential in La Venta, Mexico. Wind Engineering, 28, 225-234, **2004**.
21. PERSON, A. User guide to ECMWF forecast products. ECMWF. Págs. 129. Yang, F., H. Pan, S. K. Krueger, S. Moorthi y S. J. Lord, 2005. Evaluation of the NCEP Global Forecast System at the ARM SGP site. Monthly weather review. 134, 3668-3690, **2013**.
22. Peter Lynch. The Emergence of Numerical Weather Prediction: Richardson's Dream. 32 Avenue of the Americas, New York NY 10013-2473, USA: Cambridge University Press, **2014**.
23. P. Louka, G. Galanis, N. Siebert, G. Kariniotakis, P. Katsafados, I. Pytharoulis and G. Kallos. Improvements in wind speed forecasts for wind power prediction purposes using Kalman filtering. Journal of Wind Engineering and Industrial Aerodynamics 96, 2348– 2362, **2008**.
24. Rafael Andrés Lighezzolo. Integración de modelos numéricos de predicción meteorológica en sistemas de alerta temprana a emergencias. Tesis de Maestría. Universidad Nacional de Córdoba. Córdoba, Argentina, **2014**.
25. Ruiz, J. Aplicación de los pronósticos por ensambles a la predicción del tiempo a corto plazo sobre Sudamérica (Doctorado). Universidad de Buenos Aires, Facultad de Ciencias Exactas y Naturales, **2008**.
26. SENER. Prospectivas de Energías Renovables 2012-2026, **2012**.
27. Solera Ramírez, Á. EL FILTRO DE KALMAN. Costa Rica: BANCO CENTRAL DE COSTA RICA, **2003**.
28. Sugahara, S. Uma experiência com modelo estatístico (MOS) para a previsao da temperatura mínima diária do ar. Brazilian Journal of Geophysics. 18 (1) 1-14, **2000**.
29. Sweeney, C., Lynch, P., & Nolan, P. Reducing errors of wind speed forecasts by an optimal combination of post-processing methods. Meteorological Applications, 20(1), 32-40, **2011**.
30. Tusell, F. Kalman Filtering in R. Journal Of Statistical Software, 39(2), **2011**.